Distributed Data Classification in Underwater Acoustic Sensors based on Local Time-Frequency Coherence Analysis

Teodor Petrut, Cornel Ioana, D. Mauuary, Julien Mallet, Olivier Phillipe

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Teodor Petrut, Cornel Ioana
Grenoble Institute of Technology, GIPSA-lab
Saint Martin d'Hères, France
[teodor-ion.petrut, cornel.ioana]@gipsa-lab.grenoble-inp.fr

Didier Mauuary
CYBERIO
Meylan, France
didier.mauuary@cyberio-dsi.com

Julien Mallet, Olivier Phillipe
OSEAN SAS
Toulon, France
[julien.mallet, olivier.phillipe]@osean.fr

Abstract – **This paper introduces a stochastic approach that considers the distributed classification problem for a network of underwater acoustic sensors. The proposed classifier applies the third order polynomial regression to the instantaneous frequency extracted from time-frequency representation of different classes of signals and represent the polynomial's coefficients in a three-dimensional representation space. This automatic classifier is then compared to a non-parametric classifier based on the training of a standard neural network. The results of the proposed method on real data illustrate the efficiency of this algorithm, in terms of signal's characterization and lower communication bit rates between each sensor and the data center.**

Keywords — signal classification; neural network clustering; pattern recognition; distributed signal processing; time-frequency analysis.

I. INTRODUCTION

The design and the operation of networks with distributed sensors are nowadays activities that increase the operational performances of monitoring of large areas of observation. The key point in the design of distributed networks of sensors is the capacity of the distribution of signal processing algorithms that are generally aimed to detect, localize and classify the signals in the area of interest.

In our previous work [1], an architecture of network has been proposed, with processing tools based on local time-frequency coherence, at sensor level, and detection and localization, at central level. The state-of-the-art in marine intelligent sensing is the use of an energy detector (fixed or adaptive) and the estimation of the time-frequency content describing an event through either local Fourier analysis or Wavelet multi-resolution analysis. However, highly energetic efficient methods were proven to be the time-frequency coherence processing algorithms in [2]. One of the greatest advantage of this detector is that it improves the characterization of signals with fewer parameters than the previous mentioned methods. These parameters are sent out to the central processing unit that will reconstruct, for each sensor, the corresponding Instantaneous Frequency Law (IFL). The IFL is then modeled with a third order polynomial regression whose coefficients are then used for classification in a 3D space, similarly to the *K*-means clustering algorithm, frequently used as a clustering technique in a 2D space.

The paper is organized into 6 Sections. The Section 2 puts into light the time-frequency-phase coherence-based method and describes the architecture of the distributed network used for the detection, classification and localization of marine acoustical sources. The Section 3 presents the context of the classification problem and explicitly defines the classes of frequency modulated marine acoustical signals. The Section 4 presents the results of classification using a non-parametric method as it is the neural network. The Section 5 validates the proposed parametric method for classification on real-context signals acquired during an off-shore experimentation. Finally, the Section 6 compares the two methods and concludes this paper with analyzing the advantages of the proposed classification method.

II. DISTRIBUTED SIGNAL PROCESSING

The acoustic network is composed by two main elements: the set of sensors and the central-level processing unit, as seen in Fig. 1a.

Each sensor contains an embedded processing algorithm that allows the detection of a signal of interest and the extraction of the key parameters describing the signal in an analysis window W. This processing algorithm uses the time-frequency coherence analysis to locally estimate the frequency modulations in the window W.

The time-frequency-phase algorithm assumes that the signal is scanned locally with windows of N samples. For each window W, we firstly look for the local Linear Frequency Modulation (LFM) that approximate the best the local time-frequency behavior. For this purpose, the ambiguity function (*AF*) is used in the LFM estimation formula (1) which approximates the best the signal x and, eventually, the demodulation operation is applied in (2) to obtain the filtered signal [2], [3].

$$C = \frac{1}{2\tau} \arg\max_{f} \underbrace{\left| \sum x(n) x^{*}(n-\tau) e^{-i2\pi n f \cdot} \right|}_{Ambiguity\ Function} \qquad (1)$$

$$x_{filt}(t) = x(t) \cdot e^{-2\pi i \cdot Ct^{2}} \qquad (2)$$

Applying this method in the analysis for half overlapped windows of the signal, for j^{th} analyzed windows W_j, the received signal is modeled in (3) as a Polynomial Phase Signal (PPS):

$$\begin{aligned} &x_j(t) \propto e^{2\pi i \left(C_{1j} t + C_{2j} t^2\right)};\ t \in \left[jW, (j+1)W\right]; \\ &x_{j+1}(t) \propto e^{2\pi i \left(C_{1,j+1} t + C_{2,j+1} t^2\right)};\ t \in \left[(j+1)\frac{W}{2}, (j+2)\frac{W}{2}\right] \end{aligned} \qquad (3)$$

Mathematically, the detection based on the local time-frequency coherence is defined in relation (4) [1], [3].

$$\begin{aligned} &If\ d\left[\left(C_{1,j}, C_{2,j}\right), \left(C_{1,j+1}, C_{2,j+1}\right)\right] \le \delta \Rightarrow \\ &\xrightarrow{Then} \left(C_{1j}, C_{2j}\right)\ transmission \\ &\xrightarrow{Else}\ no\ transmission \end{aligned} \qquad (4)$$

where d is the Euclidian distance between the set of two coefficients estimated in two adjacent time windows. The detection is called when the distance between both coefficients sets are inferior to a statistically chosen threshold δ.

Greater improvement in detection performance and, thus, the lowering of the false alarm rate, is achieved by implementing the processing algorithm on a two-channel sensors, as illustrated in Fig. 1b. This figure illustrates the principle of distributed processing which gives better results [1]. Besides, the improvement of IFL estimation is also achieved by increasing the number of FFT frequency bins used for the computation of the Ambiguity Functions and, also, by increasing the order of approximating local polynomials.In order to do that, high computational resources are required to do massively parallel computations [7].

III. CLASSIFICATION OF MARINE ACOUSTICAL SOURCES

The key features of the proposed classification algorithm must obey to the following three rules: the acoustical sources must be described by as small as possible number of parameters, maintaining its robustness; the separation of signal modulations classes must be as clearly as possible distinguishable; the interferences phenomena must be cancelled out after the post-processing of an IFL with a polynomial regression.

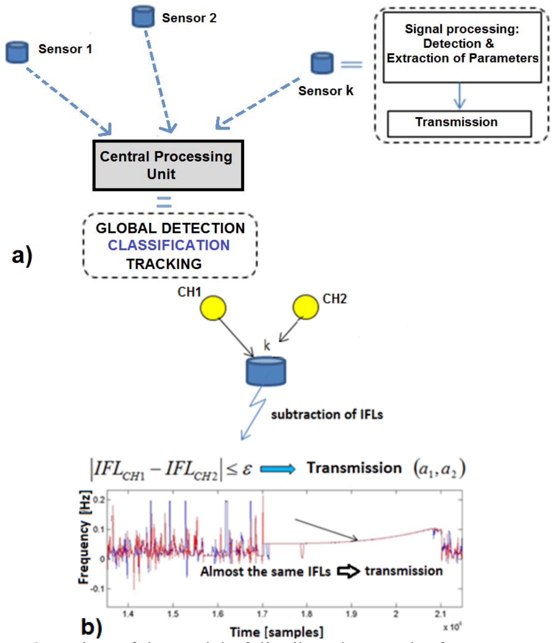


Fig. 1 **a**: Overview of the model of distributed network of sensors; **b**: Two-channel sensor model with simplified phase-based embedded algorithm, used in the experimental tests

The research study is concerned with the detection and description of the following marine acoustical sources, for which their mathematical model are defined, in the relations (5)-(8).

- *Mono-Chromatic Signals (Class C1)*, used by sonars, boat engines etc.

$$\begin{aligned} &s_j(t) = e^{2\pi i \left(C_{1j} t\right)},\ t \in \left[t_j - \frac{T_{TF}^{(j)}}{2}, t_j + \frac{T_{TF}^{(j)}}{2}\right] \\ &C_{1j} = \begin{cases} f_s,\ t \in \left[t_j, t_j + T_{TF}^{(j)}\right] \\ 0,\ t \in \left[t_j + T_{TF}^{(j)}, jT_r\right] \end{cases} C_{2j} = 0,\ C_{3j} = 0 \end{aligned} \qquad (5)$$

where T_r is the pulse repetition, $T_{TF}^{(j)}$ the duration of the IFL.

- *Linear frequency modulated signals (Class C2)*. In this case, two waveforms sub-classes are considered: a simple chirp and a double 'V' chirps.

$$s_j(t) = e^{2\pi i \left(C_{1j} t + C_{2j} t^2\right)},\ t \in \left[t_j - \frac{T_{TF}^{(j)}}{2}, t_j + \frac{T_{TF}^{(j)}}{2}\right],\ C_{3j} = 0 \qquad (6)$$

- *Second order frequency modulations (Class C3)* representing parts of mammals' vocalizations.

$$s_j(t) = e^{2\pi i \left(C_{1j} t + C_{2j} t^2 + C_{3j} t^3\right)},\ t \in \left[t_j - \frac{T_{TF}^{(j)}}{2}, t_j + \frac{T_{TF}^{(j)}}{2}\right] \qquad (7)$$

- *Third order frequency modulations (class C4)* representing also, for example, parts of underwater mammal' vocalizations;

$$s_j(t)=e^{2\pi i\left(C_{1j}t+C_{2j}t^2+C_{3j}t^3+C_{4j}t^4\right)},\ t\in\left[t_j-\frac{T_{TF}^{(j)}}{2},t_k+\frac{T_{TF}^{(j)}}{2}\right] \quad (8)$$

During research, it was revealed that the most robust regression polynomial order, which successfully obeys to the three rules, is the third order one, as also shown in the examples from the Fig. 2a-d.

The automatic signal classifier was designed to separate all the classes of frequency modulations (Classes 2-4) using the Euclidian distances between the estimated polynomial coefficients giving the order of clustering, shown in the Fig. 2e. In brief, the principle consists of processing a large amount of data and representing them in a 3D vector space by using the first three coefficients of the regression polynomial defined in the relation (9).

$$IFL_{Class\ K}=P(f)=c_{3k}t^3+c_{2k}t^2+c_{1k}t+c_{0k} \quad (9)$$

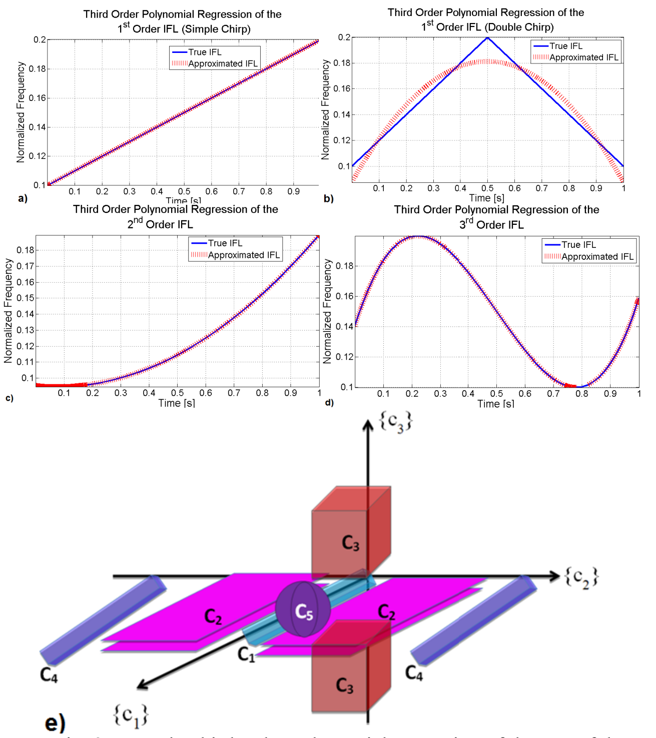


Fig. 2: **a-d.** The third order polynomial regression of the IFL of the studied signal classes; **e:** The clustering of subsets (classes) of signals in the representation space of the regression polynomial's coefficients

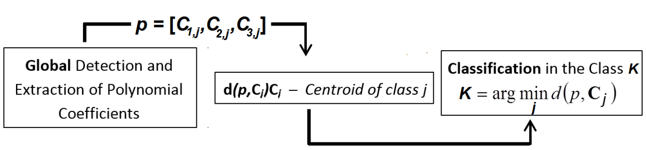


Fig. 3: Flow chart showing the proposed principle after which the classification is achieved

where *t* simply denotes the time and *P(f)* is the frequency and c_{3k}, c_{2k}, c_{1k} are the coefficients used in our proposed classification algorithm.

Thus, each IFL is located in such vector space by analyzing its Euclidian distance to the theoretical centroid coordinates, as it is shown in the flow chart of the Fig. 3. It is now clear that the classification procedure is based on using only three parameters, i.e. the polynomial regression's coefficients, instead of using all the signal's samples, as it is done in the matched filtering techniques or neural networks with supervised learning.

IV. CLASSIFICATION WITH NEURAL NETWORKS

Neural Networks (NN) techniques are widely used in linear and non-linear classification process due to their robustness to outliers and noise [6]. These are intensively used in conjunction with energy estimators based on Wavelet transforms [4], however we will adapt this model to our time-frequency-phase estimator.

Classification rules are developed using a Perceptron feed-forward network model with a single hidden layer of neurons. As schematically shown in the Fig. 4, the neural network used in this paper is composed of a single hidden neuron layer, a database with estimated IFLs and an output neuron layer. The IFLs are undersampled in order to use as small as possible number of neurons in the network's design. We tested this architecture on a database of estimated IFLs by varying the number of neurons in order to achieve a very good clustering of the IFL classes.

In Fig. 5a-b it is presented the performances in terms of Mean-Square Errors (MSE), which is the squared difference of the inputs and the outputs of the network, in the three stages mentioned in the Fig. 4. As the interest is to use as small as possible number of neurons for the sake of computation time, it is achieved that for at least 10 neurons the network gives good results. The figure 6a-b completes this section by giving the performances in terms of clustering precision of 40 IFLs, equally distributed in the 4 classes mentioned in Section 3. In Fig.6a, as the number of neurons is too small, there is 20 % error to identify the second class of IFLs (double "V" chirp). The reason is the network's failure to approximate the singularity posed by "V" curve. However, in Fig. 6b, by doubling the number of neurons, the perfect distribution of the 4 classes is obtained.

In conclusion, given its robustness with respect to noise and outliers, this approach depends on the number of samples contained in an IFL and, thus, on the number of neurons. Thus, the classification needs an extra step of finding the suitable number of neurons to correctly classify the signals.

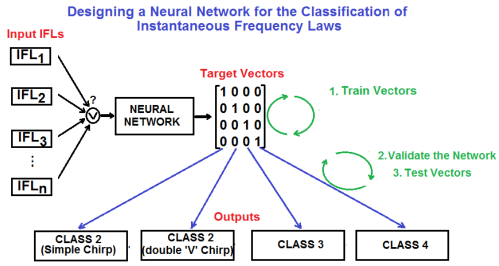


Fig. 4: Flow chart of the classification procedure showing the three typical steps during the use of a neural network: the training, synonymous with the creation of the dictionary, the validation and the test steps

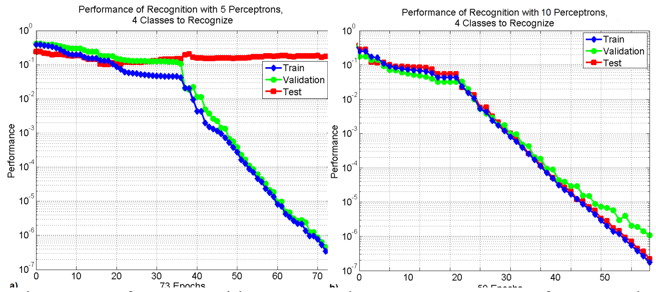


Fig. 5: **a**. Performance with respect to the mean-square errors for a neural network with 5 neurons (or perceptrons in this case): the network does not give the expected results in the testing stage, i.e. when tested with other signals than those used in the training stage; **b**. Performance in the case of a neural network with 10 neurons: the network gives much better results in the testing stage.

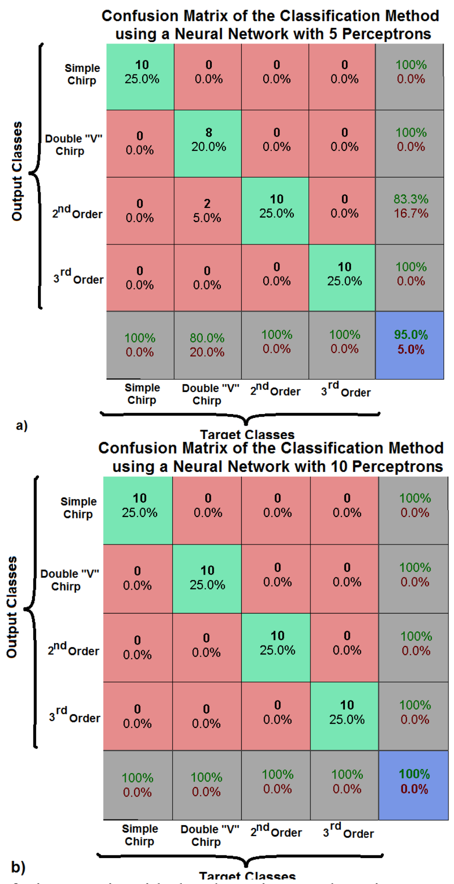


Fig. 6: **a.** Confusion matrix with the clustering results using a neural networks with 5 neurons in the hidden layer: the green boxes shows the number of the correctly identified signals and the pink boxes shows the signals wrongly identified; in this case, the results give an error of 20% when trying to identify the "V" double chirps; the overall error in this case is of 5%; **b.** Confusion matrix of the clustering results obtained with 10 neurons in the hidden layer; it is observed that each classes contains the correct number of IFLs processed during experiments

V. RESULTS

Experiments were conducted off-shore, in the Bay of Oursinières, in the South-Eastern of France, where a boat described the trajectory shown in Fig. 7 and in which perimeter there placed three passive acoustic sensors. The boat takes multiple repeated trajectories, each repetition coinciding with the emission of the following classes of signals: class 2 linear frequency modulations (chirps), class 3 second order frequency modulations and third order frequency modulations. The classes of signals emitted during experiments are shown in the Fig. 8a-d.

During experiments, it is used 3 receivers, each of them consisting of 2 hydrophones equipped with pre-amplifying blocks whose gain is 40 dB, a Blackfin DSP is used for acquisition (sampling frequency 100 kHz, acquisition period 1 s, length of analyzing window 256 samples). Also, it was used a bandpass filtering between 1.3 kHz and 48.8 kHz, and, for the local signal processing, it was used a MPPA Board © [7] for intense computations of Higher-Order Ambiguity Functions and local polynomial approximations.

One such trajectory takes 10 minutes to be completed, during which period the sensors are continuously recording data at 100 kHz sampling frequency. The boat emits one signals at each 10 seconds, 40 such emissions per one class of signals.

Once the detection algorithms at sensor level validate the presence of an acoustical source, the DSP processes the data and the radio emitter transmit the key parameters of the IFL to the central unit processing. Here, after the data fusion process, the classification algorithm is applied. The results of classification for the real signals acquired during the experiments are shown in Fig. 9a-d. We observe in these figures a good 3D grouping of data with a specifically class of frequency modulated signal. In the Fig. 10, by showing the confusion matrix it is proved the ability of this classification method to perfectly classify the studied classes.

We finally assert that the polynomial regression of the IFL constitutes a viable solution for extending the classification approach to a three-dimensional space representation, and thus increasing the separability performance between different classes of frequency modulations.

Fig. 7: One complete trajectory during the emission of a single class of frequency-modulated signals

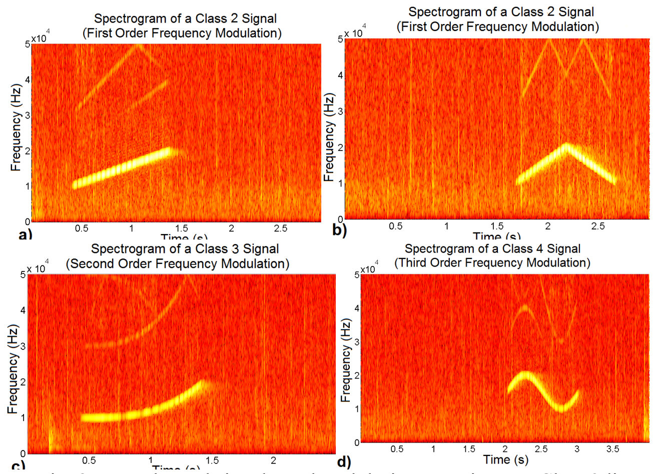
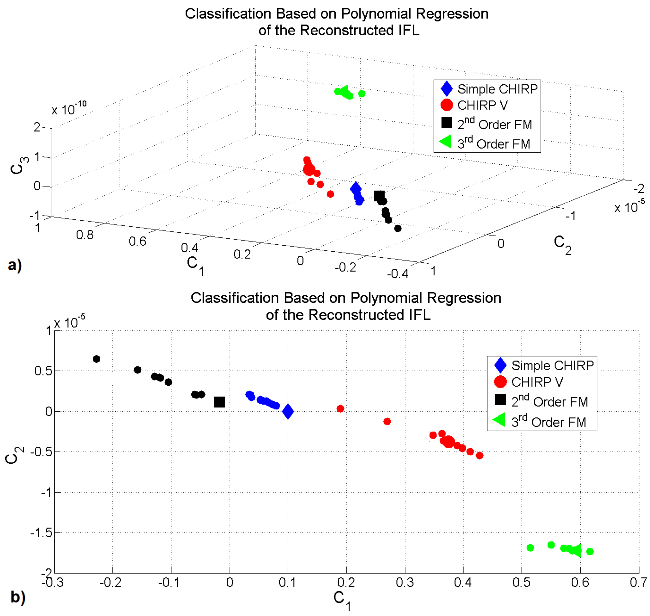


Fig. 8: **a-b**. The real signals analyzed during experiments: Class 2 linear frequency modulations (Simple Chirp and double 'V' Chirp); **c**. Class 3 second order frequency modulations; **d**. Class 4 third order frequency modulations



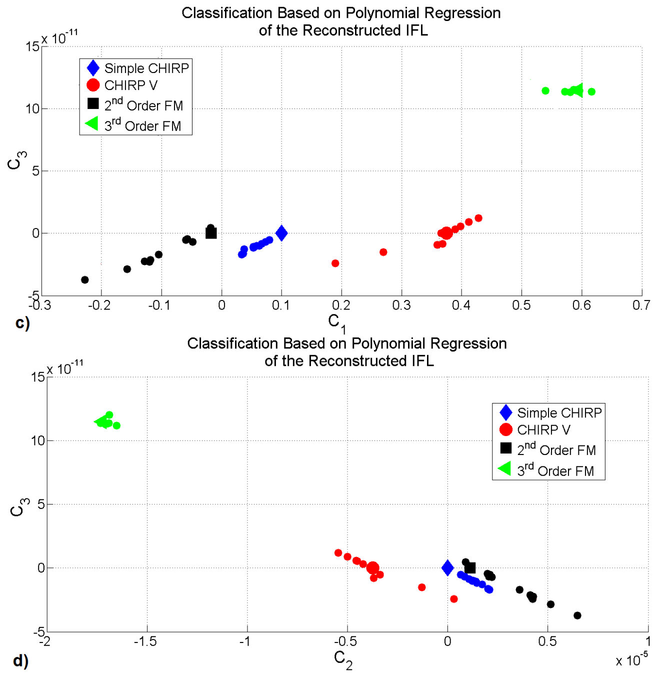


Fig.9: **a**. The results of clustering using the polynomial regression of order 3 on the reconstructed IFL at central-level processing; **b-d**. The results of classification on the projection planes

Confusion Matrix of the Classification Method using the Regression Polynomial of the IFL

	Simple Chirp	Double "V" Chirp	2nd Order	3rd Order	
Simple Chirp	**10** 25.0%	**0** 0.0%	**0** 0.0%	**0** 0.0%	100% 0.0%
Double "V" Chirp	**0** 0.0%	**10** 25.0%	**0** 0.0%	**0** 0.0%	100% 0.0%
2nd Order	**0** 0.0%	**0** 0.0%	**10** 25.0%	**0** 0.0%	100% 0.0%
3rd Order	**0** 0.0%	**0** 0.0%	**0** 0.0%	**10** 25.0%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	**100% 0.0%**

Fig. 10: The confusion matrix in the case of the 3rd order regression polynomial classification method; all the IFLs were successfully recognized and grouped into 3D clusters

VI. CONCLUSIONS

In this paper we presented a very simple and robust method for acoustical underwater signals and we proved its feasibility for marine source classification with respect to the order of frequency modulation. The greatest advantage of this method is the fact that it works in conjunction with the time-frequency-phase algorithm for the IFL estimation and its precision is proved in our experimental results. The use of a neural network in this context would be computationally cumbersome. However, improvements are required when we take into account the trains of clicks and transients used by mammals for echolocation. These improvements will consist in matching the results with a dictionary of key parameters from the time-frequency-phase algorithm.

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